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ORIGINAL ARTICLE

An ontology-driven bayesian network approach to fault diagnosis and correction in manufacturing

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Abstract
Efficient Fault Diagnosis and Correction (FDC) is crucial for maintaining high availability in manufacturing systems. This paper presents a novel ontology-driven approach for creating Bayesian Networks (BNs) to support decision-making in FDC. An ontology is developed to represent fault knowledge from domain-specific data sources, including Failure Mode, Effects, and Criticality Analysis (FMECA) data. This ontology is used as a template for creating the BN structure. The probability parameters of the BN are identified heuristically via FMECA criticality information, deterministic relationships, and expert knowledge. A case-based evaluation using an assembly line for solenoid valves demonstrates the BN's accurate FDC prediction performance.

Keywords Decision support system · Fault diagnosis and correction · Ontology · Bayesian network · FMECA

1 Introduction

One objective of manufacturing companies is to achieve a high technical availability of their manufacturing equipment to keep manufacturing costs as low as possible. To achieve a high availability, holistic fault managements aims to detect, diagnose and correct occurred faults as efficient as possible [1–3]. The objective of the fault detection step is to identify faulty process conditions indicated by deviations of measurements of characteristic properties of the process from acceptable tolerance bands [4]. During the fault diagnosis step, the root cause(s), the type, the location and the severity of the fault are identified [1, 2, 4]. The objective of the fault correction step is to make appropriate decisions about corrective measures and to carry them out to return to normal manufacturing process conditions [1, 3].

The field of fault detection and diagnosis is well researched including advanced data-driven methods that address domain-specific challenges [5, 6] and knowledge-based methods such as methods based on physical models [4, 7] or rule-based systems [4]. There exist also hybrid methods that combine multiple data-driven methods with knowledge-based methods [1, 2]. Most studies only consider the first two necessary steps of fault detection and diagnosis in holistic fault management, i.e., they neglect the subsequent step of fault correction. The focus of this work is on fault correction and the interlink with the root cause analysis and fault localization.

Manual Fault Diagnosis and Correction (FDC) processes can only be efficient and effective, if the maintenance personnel have a deep technical understanding of the manufacturing processes, a profound fault knowledge and a lot of experience in FDC. However, maintenance personnel often lack these requirements. This motivates automated decision support systems for FDC that utilize domain knowledge about the manufacturing processes and about possible faults in these processes [8–10]. The idea is to represent available fault knowledge in a knowledge base and to enable automated reasoning with this represented knowledge to derive root causes and corrective measures for an identified fault. Potential data and knowledge sources for such a knowledge base include, e.g., Failure Mode and Effect and Criticality Analysis (FMECA) documents [11, 12], historical logs

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documenting maintenance and repair operations as well as human expert knowledge.

Compared to fault detection, the root cause analysis and fault correction relies heavily on the utilization of knowledge models [13]. However, the utilization of knowledge in fault correction is less commonly understood due to the wide variety of different data and knowledge sources and the highly application-dependent solution approaches. There are also open research questions regarding the identification of relevant fault information and knowledge sources required for decision support to FDC [10, 14]. Known knowledge-based methods in decision support systems include for example simple rule-based and case-based approaches, frequent itemset mining, search and query approaches, semantic web technologies, Bayesian Networks (BNs), as well as large language models (LLMs) [8, 13, 15, 16]. BNs enable the modeling of cause-and-effect relationships, the integration of expert knowledge in form of the network structure and probability parameters as well as causal, probabilistic reasoning taking uncertainty into consideration [17, 18]. Compared to related methods, these are remarkable advantages of BNs, which fulfill important requirements of decision support systems for FDC [10, 14]. Hence, the proposed approach of this work is based on BNs.

Several works exist that use BNs for fault knowledge representation and reasoning in FDC [19–25]. These approaches are mostly application-specific and are tailored to only one or two specific data or knowledge sources. So, there is a need for research on generic knowledge models that uniformly describe fault knowledge originating from different data and knowledge sources. The BN approaches from related works are mainly developed for fault diagnosis and root cause analysis. Corrective measures are not explicitly modeled in the BN structure. Hence, approaches supporting fault correction only exist in a broader sense, if measures can be derived implicitly from decision recommendations regarding root causes. In related work, the probability parameters of the BNs are mainly defined manually by experts, which is an elaborate task. The decision performance of BNs with manually defined parameters often suffers from the subjectivity of the experts. Here, further research is needed to automatically identify the probability parameters by using as much prior information as possible from domain-specific data and knowledge sources. Furthermore, the evaluation procedures used in related works are limited to case studies with a maximum of one or two sample fault cases, i.e., they do not evaluate the decision behavior of the proposed BNs with respect to the actual inference requirements in FDC.

In this work, we present a novel and generic ontology-driven BN approach for decision support on FDC by leveraging multiple data and knowledge sources. For observed faults, the BN developed allows the derivation of the most probable fault effects, root causes and suitable corrective measures. Our approach addresses the above-mentioned open research gaps through the following novel contributions:

(1) A generic ontology for FDC that enables the unified modeling of fault knowledge from different domain-specific data and knowledge sources such as FMECA data.
(2) An application-independent and automated method to create the structure of a BN representing the fault knowledge modeled by the proposed ontology. Thereby, the proposed ontology is used for a semantic data integration and the derivation of the causal structure of the BN. Compared to related works, our BN explicitly supports fault correction by modeling corrective measures as well as the associated fault root causes and the system hierarchy in the BN structure.
(3) A novel heuristic parameter identification approach that automatically determines the probability parameters of the created BN by leveraging prior information from FMECA data, i.e., criticality information and deterministic fault relationships. In this way, our approach reduces the influence of expert subjectivity in parameter identification compared to related work.
(4) A comprehensive case-based evaluation of the proposed approach with a case study of a highly automated assembly line. The prediction performance of the BN is systematically evaluated based on 25 sample fault cases across six inference objectives that are relevant for FDC.

The results of the case study show that our proposed approach enables an efficient reuse of existing data and knowledge sources for decision support on FDC. The case-based evaluation of the prediction performance of the BN demonstrates a success rate of $100\,\%$, i.e., the decision behavior of the BN is equivalent to that of highly experienced domain experts, which leads to precise decisions for FDC. A conducted sensitivity analysis shows that the BN developed enables clear decisions that are very robust to changes in the underlying parameters. The computational performance analysis confirms that the creation of the BN structure, the heuristic parameter identification approach as well as the inference step have very efficient computational runtimes.

The rest of the paper is structured as follows: Section 2 introduces the background of our paper. In Section 3, the concept and methodology of our approach is presented. The approach to create the BN structure via the proposed ontology is described in Section 4. Section 5 presents the novel heuristic parameter identification approach. The results of the case study are presented and discussed in Section 6. In addition, we also compare our approach to related work in Section 6. Section 7 concludes the work.

2 Background

This section introduces the methodological background of this work.

2.1 Data and knowledge sources for FDC in manufacturing

Data and knowledge sources in manufacturing that are relevant for FDC comprise FMECA data, digital logbooks of historical maintenance tasks, 8D reports, as well as heuristic and empirical expert knowledge. These data and knowledge sources typically include the following fundamental data and semantic relations for FDC:

- Cause and effect relationships between faults, fault effects, root causes and proper actions to correct them.
- Inter-causal relationships along fault chains.
- Hierarchy and composition of the manufacturing system to enable fault localization.
- Frequency of fault cases, e.g., a root cause A occurs n times and causes the fault effect B m times.
- Severity and relevance of fault cases.

Domain knowledge for FDC is typically available in different forms, with weakly defined semantics and inadequately represented causal relations. Often, it needs to be manually formalized to be represented in a knowledge base [26, 27]. In addition, corresponding data sources are usually isolated and have poor data quality. This makes it difficult to share and reuse fault knowledge for FDC via a knowledge base.

Since we integrate FMECA data via the proposed ontology-driven approach into a BN, we introduce FMECAs as a special knowledge source in the following Section 2.2.

2.2 Failure mode and effect and criticality analysis

Nowadays, the Failure Mode and Effect Analysis (FMEA) is a standardized technique of the quality management for the reliability, safety and risk analysis for any kind of objects such as systems, components or processes [11, 28]. The standard FMEA is a qualitative analysis technique. The criticality analysis extends it to the Failure Mode and Effect and Criticality Analysis (FMECA) that quantitatively assesses the fault effects and the relative importance of failure modes [11]. In this work, we follow the FMECA standard according to the AIAG & VDA FMEA FMEA handbook [12, 28]. According to this standard, Table 1 shows the relevant data fields of three sample failure mode entries of a FMECA used within this work. This FMECA worksheet includes the following elements:

System element & functional unit A *System Element (SE)* or *Functional Unit (FU)* is an unit of analysis that performs or is intended to fulfill none, one or multiple functions.

Function Describes the *Function (F)* of a SE or FU.

Failure mode *Failure Modes (FM)* correspond to a fault, malfunction or defect of a SE or FU [11, 28]. All FMs of a FMECA are considered as being independent of each other.

Fault root cause One or multiple *Fault Root Causes (FC)* can cause a FM.

Fault effect The *Fault Effect (FE)* is the result of one or multiple FMs for one or multiple FUs. It describes how a function (F) or the state of a FU or SE is influenced by the

Table 1 Two sample fault instances (column I) including three failure modes of a FMECA

I	System Element (SE)	Functional Unit (FU)	Function (F)	Fault Effect (FE)	S	Failure Mode (FM)	Fault Root Cause (FC)	O	Corrective Measure (CM)
1	**SE01**: Valve Assembly Line **SE02**: Cell02 **SE03**: Station01	**FU01**: Process greasing housing cartridge bore	**F01**: Greasing	**FE01**: Valve switching times not reached	5	**FM01**: Grease incorrectly dispensed	**FC01**: Air inclusions in the grease	3	**CM01**: Change grease
				FE02: Cartridge bore not completely greased	7		**FC02**: Grease plugs clogged	4	**CM02**: Clean grease plugs
2	**SE01**: Valve Assembly Line **SE02**: Cell02 **SE04**: Station02	**FU02**: Process pressing in cartridges	**F02**: Positioning cartridges	**FE03**: Failure valve, no switching of air	8	**FM02**: Not pressed in position	**FC03**: Press-in force too low	2	**CM03**: Check and adapt settings
				FE04: Control head is pressurised	5				
				FE03: Failure valve, no switching of air	8	**FM03**: Surface of cartridge bore damaged	**FC04**: Cartridge bore not completely greased	6	**CM04**: Check and repair greasing process
							FC05: Incorrect press settings	3	**CM03**: Check and adapt settings
...	...	...	...	...	...	...	...	...	...

FM [11]. Note that the effects of a FM can propagate via fault chains, i.e., they can result in FCs of further FMs [11].

Preventive & corrective measures Preventive measures are used to reduce or prevent the FEs of a FM. They are related to FCs. If maintenance actions for the prevention of FMs are known, these should also be mentioned here [11]. There exist also FMECAs that document *Corrective Measures (CM)* [22, 29]. In this work, just corrective measures are considered (cf. Table 1). If a FEMCA does not contain corrective measures, domain experts can easily extract information about corrective measures using the entries for FCs and preventive measures in the FMECAs, e.g., during a data integration step.

Criticality analysis The criticality is a numerical index that indicates the severity of a failure or fault in relation to the occurrence probability. The criticality is typically defined via the Risk Priority Number $\mathrm{RPN} = S \cdot O \cdot D$ [11, 28]. Here, *S* is the estimated severity of a FE of a FM for the overall system. FCs leading to the same fault sequence are assigned the same severity *S*. The factor *O* is the occurrence probability of the FC of a FM taking into account the preventive action. The factor *D* is the detection probability of the FC, FM or FE. Each of the three factors is usually estimated as a rank number on an ordinal scale ranging from 1 to 10, so that $\mathrm{RPN} \in [1, 1000]$. The greater the value of the RPN, the higher the risk [11]. Note that different values of *S*, *O* and *D* may lead to the same RPN. This may distort the risk implications of FMs if only the RPN is taken into consideration [11, 30].

2.3 Bayesian networks

A BN is a probabilistic model in form of a Directed Acyclic Graph (DAG) $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, with the set of nodes $\mathcal{V}$ and the set of directed edges $\mathcal{E}$ [17, 18]. The nodes of a BN represent a set of random variables $\boldsymbol{X} = \{X_1, ..., X_n\}$ and the directed edges correspond to causal relationships between these variables. In this work, we consider BNs whose variables represent discrete probability distributions that are typically defined via Conditional Probability Tables (CPTs) of child nodes and prior probabilities of parent nodes [17]. Each variable X_i has $r_i \geq 2$ states $Val(X_i) = \{x_i^1, ..., x_i^k, ...,$ $x_i^{r_i}\}$. A parameter $\theta_{ijk} \in \boldsymbol{\theta}_i$ of a child node corresponds to the probability that its random variable X_i is in state *k* if the configuration of the states of the parent nodes, given by $\mathrm{pa}_{\mathcal{G}}(X_i)$, is in the *j*-th configuration pa_i^j:

$$\begin{aligned} P\left(X_i = x_i^k \mid \mathrm{pa}_i^j, \boldsymbol{\theta}_i\right) = \theta_{ijk} \ , \\ \text{for } k = 1, \ldots, r_i \ , \\ j = 1, \ldots, q_i \text{ and } q_i = \textstyle\prod_{X_j \in \mathrm{pa}_{\mathcal{G}}(X_i)} r_j \quad . \end{aligned} \tag{1}$$

Here, $Val\left(\mathrm{pa}_{\mathcal{G}}(X_i)\right) = \{\mathrm{pa}_i^1, \mathrm{pa}_i^2, ..., \mathrm{pa}_i^j, ..., \mathrm{pa}_i^{q_i}\}$ with a systematic order of the q_i configurations of the states of the parent nodes [18, 31]. The overall BN describes a multivariate probability distribution that enables probabilistic reasoning. If evidence of the current states of one or multiple probability variables is available, e.g. by observing an event, the posterior probabilities of unobserved variables can be calculated using exact or approximate inference algorithms [18, 31].

If the structure of a BN is specified, the probability distributions of the nodes must be determined via (1) parameter learning algorithms, (2) expert knowledge and/or (3) empirical data (e.g., reliability data) [32]. Generally, expert knowledge is used to manually specify the probability parameters if no appropriate data sources are available for parameter learning or when the BN is rather qualitative and difficult to learn.

3 Concept & methodology

We propose a novel decision support approach to FDC that realizes the knowledge representation and automated reasoning via an ontology and a BN. This approach is intended to support maintenance personnel in manufacturing with FDC. The basis for the design considerations and the development of our proposed approach are the six most relevant inference objectives ($\mathrm{IO_x}$) that a decision support system for FDC must fulfill:

- IO_1: Identification of the most probable root cause for an identified fault: *Failure Mode → Root Cause*.
- IO_2: Identification of the most probable fault and fault effect for an identified root cause: *Root Cause → Failure Mode → Fault Effect*.
- IO_3: Prediction of a corrective measure that is most likely to correct a fault or root cause: *Failure Mode → Root Cause → Corrective Measure*.
- IO_4: Identification of the most probable fault and root cause for an identified fault effect: *Fault Effect → Failure Mode → Root Cause*.
- IO_5: Traceability of causal chains between multiple faults, their fault effects and root causes: *Failure Mode 1 → Fault Effect → Root Cause → Failure Mode 2*.
- IO_6: Localization of faults and root causes in complex structures of manufacturing equipment: *Root Cause → Failure Mode → Fault Effect → Functional Unit / Component → System Element*.

We identified these six IO_x via a requirements analysis that we conducted together with maintenance personnel of our industry partner, the Festo SE & Co. KG. We use a BN to fuse fault knowledge from different data and knowledge sources. Figure 1 provides a conceptual overview of our proposed approach.

3.1 Data & knowledge level

The data and knowledge sources containing the fault cases for building the knowledge base are located in the data and knowledge level. A fault case may for example be represented by one entry for a corresponding fault scenario of a component or process in the FMECA data. Domain experts may define further fault cases by formalizing their expert knowledge.

3.2 Knowledge engineering level

The component of the knowledge base and automated reasoning in the *knowledge engineering level* orchestrates the overall system including the semantic data integration, creation of the BN, provisioning of fault information and probability predictions of the BN for the interaction level. The basis for creating the knowledge base is the domain-specific *generic ontology for FDC* (see Section 3.3). It has two essential roles. Firstly, it is used within the data integration approach to build an integrated dataset containing the fault cases from the underlying data and knowledge sources. Secondly, it serves as a template to create the structure of the BN by integrating the fault cases of the integrated dataset into the BN (cf. Section 4). As outlined later in Section 6.5.2 on related work, there is a need for further research in the automated use of prior information from domain-specific data and knowledge sources, such as FMECA data, to improve the inference performance of BNs by reducing the bias of the probability parameters estimated by experts. We addressed this research gap by developing a novel heuristic parameter identification approach using prior information from the FMECAs data such as criticality information and deterministic relationships to automatically determine the probability parameters of the BN (cf. Section 5).

The resulting BN enables probabilistic reasoning with the represented fault knowledge and with regard to the defined six inference objectives. For example, observed FEs and/or FCs can be entered into the BN as evidence. Subsequently, the posterior probability distribution of the BN can be recalculated to derive the most probable FM, FE, FC or CM.

3.3 Generic ontology for fault diagnosis and correction

Our proposed ontology-driven approach addresses the challenges to represent knowledge from multiple heterogeneous data and knowledge sources mentioned in Section 2.1. We developed an ontology that consists of an application-independent top-level ontology and an application-specific customized ontology. Figure 2 shows the ontology for the assembly line of our case study (cf. Section 6) modeled as an UML class diagram.

The top-level ontology is a declarative abstraction hierarchy that defines the fundamental concepts, associations and cardinalities for the modeling of the FDC domain [33, 34]. We derived it based on the fundamental concepts and causal relations in the FDC domain, as well as on the sample fault cases contained in the considered data and knowledge sources. It represents the causal model of the fault behavior of a manufacturing process or a component including seven concepts and the relational dependencies between them: *System Element (SE)*, *Functional Unit (FU)*, *Function (F)*, *Failure Mode (FM)*, *Fault Effect (FE)*, *Fault Root Cause (FC)* and *Corrective Measure (CM)*. Here, the FU is a generic concept that corresponds to the two specialized concepts of a *Process* and a *Component*. Each FU may have or fulfill 0..* functions *F*. There exist also components that do not directly fulfill

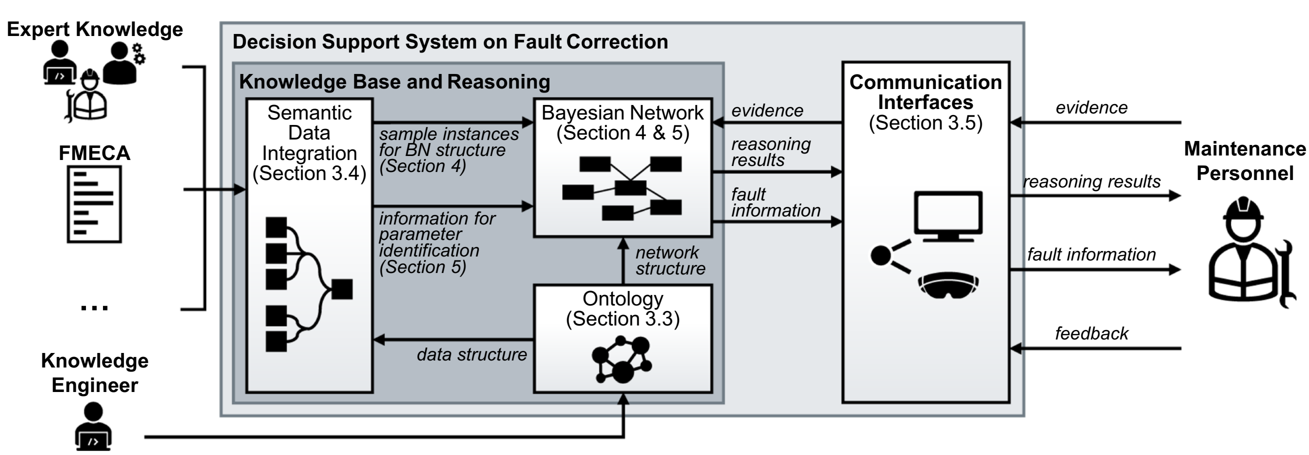


Fig. 1 Overview of the devised ontology-driven BN approach to decision support on FDC

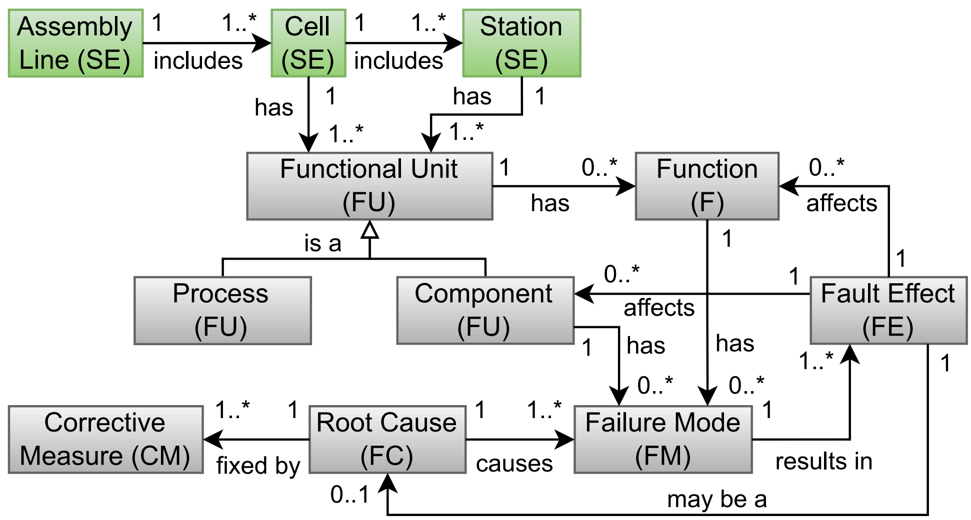


Fig. 2 The proposed generic ontology for FDC in manufacturing. The concepts of the generic top-level ontology are depicted in gray. The concepts of the application-dependent customized ontology, which is adapted for the assembly line of the considered use case, are highlighted in green

a function F in terms of a manufacturing process, but can still fail. For example, a sealing can cause a cylinder leakage due to wear out. Such fault scenarios of single components (worn out sealing) are also modeled by some types of FMECAs (cf. Section 2.2) and thus are considered in the proposed ontology. Each function F or component without a function may have $0..^{*}$ failure modes. Typically, a failure mode FM is part of the fault chain FC → FM → FE. We extended this fault chain by the relation CM ← FC to directly derive suitable corrective measures for an occurred fault root cause FC. In this way, compared to related work, our devised BN approach explicitly provides decision support for fault diagnosis, root cause analysis, and fault correction. The concepts and associations modeled by the top-level ontology even allow the representation of fault chains, i.e., chained faults where the FE of one FM is simultaneously the FC of another FM.

Data and knowledge sources of different use cases can have different content and knowledge structures with regard to FDC. Figure 2 therefore shows how an application-specific ontology (green) may extend the generic top-level ontology (gray) by application-specific concepts for the system hierarchy of the assembly line. Each cell and station of the system hierarchy of the assembly line has $1..^{*}$ functional units that in turn are modeled by the generic top-level ontology.

The overall ontology describes a unique *fault instance* comprising multiple instances of the concepts modeled by the ontology. A fault instance can be seen as the smallest unit that is integrated into the BN structure via the BN creation process (cf. Section 4). In FMECA data, for example, a fault instance is given for each functional unit and function for which the associated fields of FEs, FMs, FCs and CMs satisfies the the minimum cardinalities of the ontology. Table 1 shows two sample fault instances in the considered FMECA data.

Compared to related work (cf. Section 6.5), our proposed ontology is a generic knowledge model that uniformly describes the fault knowledge originating from different data and knowledge sources. The top-level ontology describes fault knowledge for FDC in a generic and application-independent way. The application-specific ontology, once modeled for an underlying application, can be applied using multiple data sources such as FMECA data and historic maintenance data related to the respective application. Our ontology fosters the sharing and reusability of fault knowledge [8, 33].

3.4 Semantic data integration

The objective of the semantic data integration according to Fig. 1 is to integrate the fault cases from the various data and knowledge sources into a consolidated dataset with a standardized data structure. This consolidated dataset may then be used to derive the fault instances for creating the BN. The data integration approach for the FMECA data is based on semi-automatic steps. The data from the FMECA fields SE, FU, F, FE, FM, FC, CM, S and O are automatically integrated into the target data structure using state-of-the-art methods of information integration [35]. If a FMECA does not explicitly contain a CM field, the CMs of a fault case are manually derived from the FMECA entries on FCs and preventive actions (cf. Section 2.2). In the context of a FU and FM, it is easily possible for domain experts to identify the CM for a FM from the associated entries for the FC and preventive action. These two data fields typically contain enough relevant information about root causes and fault characteristic that experts can use to derive CMs via their expert knowledge. To further extend the number of fault instances and to improve the quality of existing fault instances, we also elicited the heuristical and empirical knowledge from maintenance personnel and added it to the integrated database.

The data integration step is key to ensure semantic consistency of the integrated dataset and practical applicability of the BN construction process. In industrial practice, FMECAs are often conducted by different engineers over time, which may lead to inconsistencies, word sense ambiguity and missing entries. To address these challenges, the data integration incorporates several preprocessing and data validation mechanisms. First, we use a fault dictionary that maps semantically similar terms (e.g., synonyms and abbreviations) to unified ontology concepts. This ensures consistent node creation and linkage during BN construction. Second, we apply automated spell- and grammar-checking routines to reduce incorrect text in the input data. Third, the data integration approach performs checks to validate the schema of the data and the completeness of the fault instances. If missing mandatory fields are detected (e.g., missing risk priority numbers or missing CMs), the user can manually complete the missing information or reject the related fault instance. These mechanisms improve the robustness of the approach and ensure that the resulting BN models are both semantically coherent and structurally complete, even when the underlying FMECA data formats are heterogeneous. Future work may further improve and automate the consistency checks and completion of incomplete FMECA data by using generative models for natural language processing.

3.5 Interaction level

The interaction level includes the components for the communication with the BN, e.g., via a REST API. The communication interfaces enable the users to enter evidence into the BN. Subsequently, the communication interfaces retrieve the FDC reasoning results and further fault information. It is also possible to integrate user feedback with respect to the decision recommendations. This feedback may be used to continuously improve the decision-making performance of the BN.

3.6 Prototypical implementation

We implemented all of the concepts and methods developed in form of a software system called *Bayesian Decision Support Network for Fault Diagnosis and Correction (BDSN-FDC)*. The algorithms for creating the BN based on the integrated dataset and the heuristical parameter identification approach are implemented with the Python programming language (version 3.9.9) as well as with the software tools *SMILE Engine* with *PySMILE*[1] (version 2.4.0) and *GeNIe Modeler*[2] (version 5.0.5310.0) from BayesFusion, LLC. We have made all implementations available on GitHub[3].

4 Creation of the bayesian network structure

The causality model described by the generic ontology enables reasoning and explanation of fault mechanisms for FDC. The fault instances of the ontology in the integrated dataset represent fault knowledge which is predestined for solving FDC problems. The BN to be created integrates both the causal relations and the fault instances via its structure. In the following, we present the steps to create the BN structure using the integrated dataset and the generic ontology for FDC. The prerequisites for the network creation are a semantically consistent integrated dataset (cf. Section 3.4) that includes one or multiple complete fault instances. A fault instance is considered complete, if it satisfies the minimum cardinalities defined by the ontology in Fig. 2. For example, each failure mode must be associated with at least one fault effect and one root cause.

The resulting DAG of the BN represents conceptually meaningful variables and states via its nodes as well as causal relationships between the variables via its edges, this way making the BN to a globally consistent knowledge base [17]. For a better understanding, Fig. 3 shows an exemplary part of the BN structure resulting after executing the following steps for the two sample fault instances from the FMECA data of the considered case study (cf. Table1).

1) **Add functional units:** All unique FUs in the integrated dataset are identified and added to the BN structure as a node $X_{\mathrm{FU},i}$ with $Val\left(X_{\mathrm{FU},i}\right) = \{\mathrm{OK}, \mathrm{NOK}\}$. These node states represent whether the relevant FUs are functional (OK) or not (NOK).
2) **Add functions and failure modes of a functional unit:** Based on the integrated dataset, the set of associated functions is determined for each unique FU. For each identified function F, a multi-state node $X_{\mathrm{F},i}$ with $Val\left(X_{\mathrm{F},i}\right) = \{\mathrm{FM}_1, ..., \mathrm{FM}_i, ..., \mathrm{FM}_q, \mathrm{UNK}, \mathrm{OK}\}$ is added to the BN. These $(q+2)$ states represent the individual q failure modes FM_i, one unknown state UNK and the fault-free, normal state OK of the function F. A FM is regarded as a (faulty) state of a function (cf. Fig. 2). This modeling schema ensures that the discrete

[1] BayesFusion SMILE Engine (https://www.bayesfusion.com/smile)

[2] BayesFusion GeNIe (https://www.bayesfusion.com/genie)

[3] BDSN-FDC (https://github.com/IPVS-AS/BDSN-FDC)

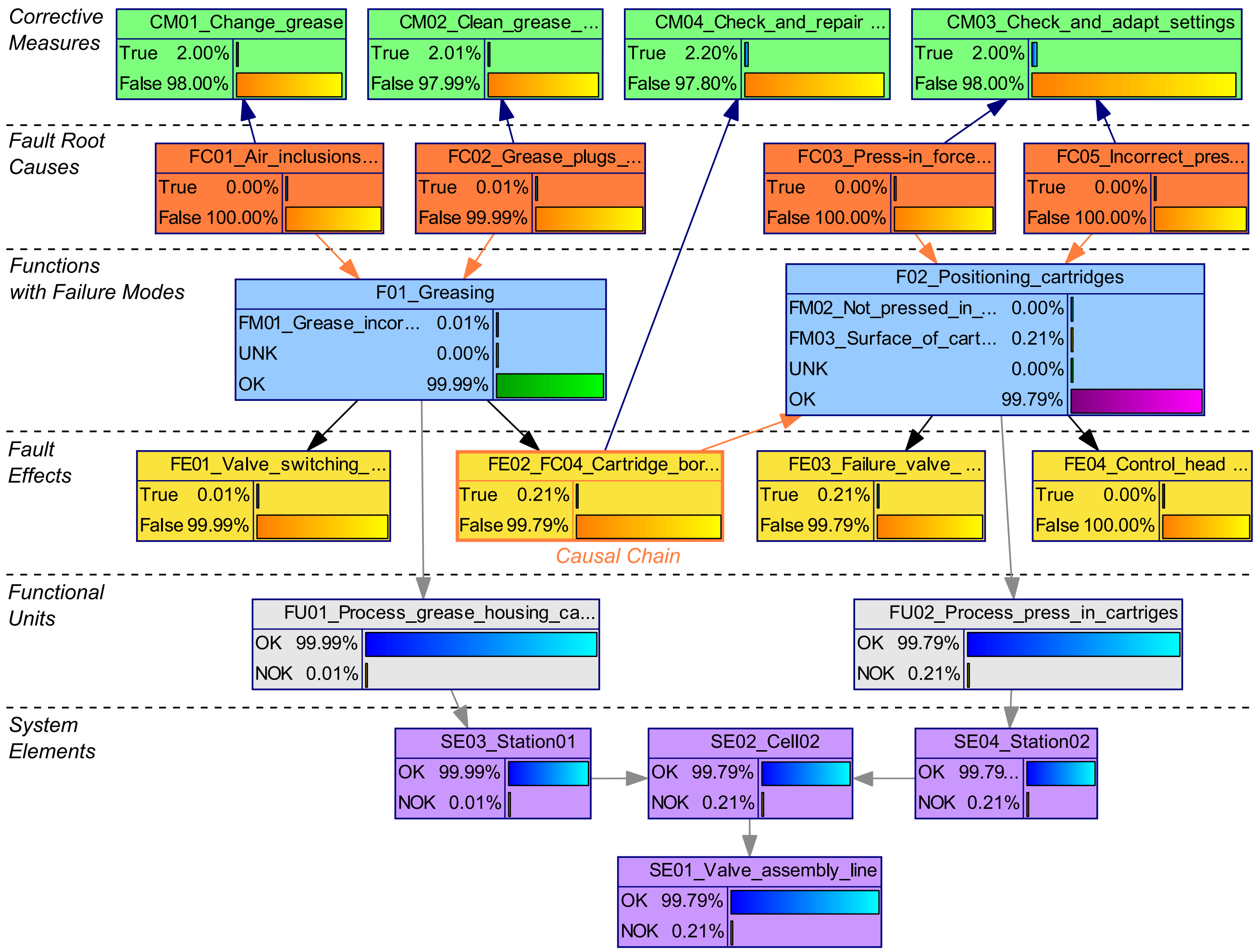


Fig. 3 Exemplary BN structure created with the proposed ontology-driven approach. The example structure and the color scheme is based on the example FEMCA entries given in Table 1. Meaning of the node colors: ☐ : SE, ☐ : FU, ☐ : FE, ☐ : F with FMs, ☐ : FC and ☐ : CM

states of multi-state nodes are complete and mutually exclusive [31, 36]. Noisy max nodes [37] are used to model the nodes of functions. By doing so, the number of probability parameters to be determined is reduced. According to our ontology (Fig. 2), components may exist that have no functions but can still have failure modes. Such nodes of components are added to the BN in the same way as the nodes of functions of a functional unit, as described in this step.

3) **Add fault root causes:** Each unique FC in the integrated dataset is added to the BN as a binary node $X_{\mathrm{FC},i}$ with $Val(X_{\mathrm{FC},i}) = \{\mathrm{True}, \mathrm{False}\}$. The nodes representing FCs are root nodes in the BN. According to our ontology, each FC causes $1 : n$ FMs of several functions of FUs or components. These causal relations are modeled as directed edges between FCs and FUs in the BN. If a FC only causes one or a subset of FMs of a node representing a function or component, the explicit mapping of the FC to the associated FMs is achieved via the conditional probability parameters of the child nodes (cf. Section 5).
4) **Add fault effects:** Each unique FE in the integrated dataset is added to the BN as a binary node $X_{\mathrm{FE},i}$ with $Val(X_{\mathrm{FE},i}) = \{\mathrm{True}, \mathrm{False}\}$. According to the ontology, FMs evoke $1 : n$ FEs. Since FMs are modeled as state variables of FUs or of components, we extend the BN by directed edges pointing from nodes of FUs or components to the associated nodes of FEs. The nodes of FEs have to model a multi-label problem, because one FM can evoke several FEs simultaneously. Such an independent occurrence of multiple FEs can be implemented using binary nodes. The explicit mapping of the FMs and the corresponding FEs that they evoke is controlled via the conditional probability parameters of the FE nodes (cf. Section 5).
5) **Add corrective measures:** Each unique CM in the integrated dataset is added to the BN as a binary node $X_{\mathrm{CM},i}$ with $Val(X_{\mathrm{CM},i}) = \{\mathrm{True}, \mathrm{False}\}$. According

to the top-level ontology, a fault root cause can be fixed by 1 : *n* corrective measures. Hence, the nodes $X_{\mathrm{CM},i}$ are specified as child nodes of the nodes $X_{\mathrm{FC},j}$ for fault causes in the BN.

6) **Add the system hierarchy:** The composition of the system consists of multiple SEs that are ordered in a certain hierarchy. Each FU belongs to one SE. For each SE, we add a binary node $X_{\mathrm{SE},i}$ with $Val\left(X_{\mathrm{SE},i}\right) = \{\mathrm{OK}, \mathrm{NOK}\}$ to the BN. The directed edges between the nodes of SEs as well as between the nodes of SEs and FUs follow the associations modeled by the customized ontology. The structure of the underlying system is known at the time the BN is created. In addition, we know a priori how the system states are aggregated along the system hierarchy. If, for example, the process step *FU02* in the BN is affected by a fault (state NOK), this state is adopted for the higher-level SE nodes *SE04*, *SE02* and *SE01* (cf. Table 1 and Fig. 3). Based on this prior information and deterministic relationships, the nodes of SEs and FUs can be modeled using deterministic nodes. This modeling schema enables the fault localization (IO_6).

7) **Causal chains:** Since FEs of a FM may be the FCs of further FMs, the BN must be able to model such causal chains including FEs and FCs of different FMs (IO_5). We realize such causal chains via a binary node that represent simultaneously both a FE of a node of a function or component as well as a FC of a further node of a function or component (cf. node FE02_FC04 marked orange in Fig. 3). This binary node has the two states True and False.

A novel contribution of our approach is the ontology-driven generation of the BN structure. As illustrated by Fig. 3, the created BN structure represents the typical causal relations FCs → FMs → FEs. This causal structure is already known in the related works [19–22, 38]. Our novel contribution to this modeling scheme is that we model the FMs as states of a multi-state node representing a function or a component. A further novel contribution are the nodes of CMs, which have a causal relationship from FC nodes to explicitly derive CMs for a fault case. This way, the BN can be used not only for fault diagnosis and root cause analysis, but also for decision support on fault correction. Explicitly modeling the hierarchy of the underlying system via deterministic binary nodes in the BN is likewise a novel contribution, as it enables fault localization.

5 Heuristic parameter identification approach

In this section, we present our heuristic parameter identification approach for the BN that we created via the ontology-driven approach and using FMECA data. Our approach is based on three methodological concepts that aim to determine probability parameters that meet the inference objectives according to Section 3. The first concept utilizes criticality information from the FMECA data such as the severity *S* and occurrence probability *O* via several heuristic calculation rules to prioritize the FCs, FMs and FEs of fault instances relative to each other. The second concept leverages deterministic relationships available in the FMECA data to define the conditional probabilities between the causal structures of FUs, Fs, CMs, FCs, FMs and FEs. In addition, the deterministic relationships are exploited along the SEs of the system hierarchy to enable fault localization. These first two concepts are preferably used to leverage the prior information provided by the FMECA data for parameter identification. Only in cases where the probability parameters cannot be determined using these two concepts is the third concept applied. It is a qualitative approach where domain experts estimate the probability parameters. Thereby, the experts align their estimates along a verbal scale that maps the probability values to verbal probabilistic expressions (cf. Fig. 8 in the appendix), e.g., the term "certain" is associated to the probability of $90\,\%$. Such a verbal scale ensures that domain experts provide comparable and consistent assessments of the probability of events [31, 39, 40].

Our parameter identification approach necessitates two prerequisites. Firstly, the BN structure must consist of nodes that represent complete fault instances, as already discussed in Section 4. Secondly, for each FE node, FC node and interlinked failure modes, the associated occurrence probabilities (*O*) and severity values (*S*) must be available in the integrated dataset. If these two prerequisites are not met, the automated heuristic parameter identification approach cannot be executed for the affected nodes of a fault instance. In such cases, the user must manually define the probability parameters of the affected nodes.

Compared to related work that mainly uses expert knowledge and only little prior information from FMECA data (cf. Section 6.5.2), we leverage much more of the criticality information and deterministic relationships available in FMECA data for parameter identification. In the following, the six steps of our parameter identification approach are presented in more detail (order is irrelevant):

1) **A priori probabilities of FC nodes:** The a priori probabilities of the two states (True, False) of the root nodes $X_{\mathrm{FC},i}$ are calculated using the occurrence probability O_i from the underlying FMECA data. This functional mapping is plotted in Fig. 4. The probability parameters are then defined as:

	True	False
$P\left(X_{\mathrm{FC},i}\right)$	$p_{\mathrm{O}}\left(O_i\right)$	$1 - p_{\mathrm{O}}\left(O_i\right)$

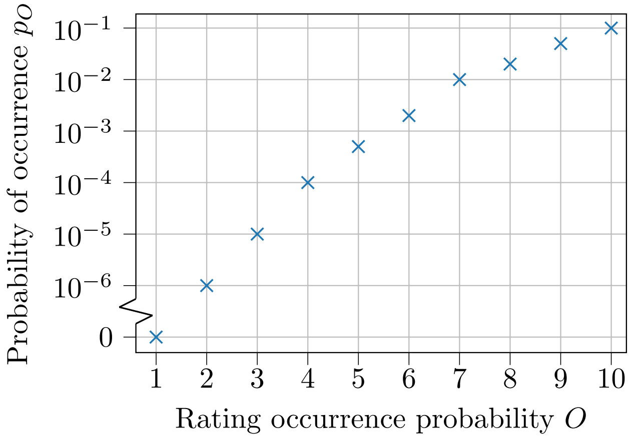


Fig. 4 Probability values for the ordinal occurrence probability O of fault causes according to the AIAG & VDA FMEA handbook [12, 28]

2) **CPTs of F nodes:** The parameterization of the CPT of the probability variable of a function $X_{\mathrm{F},i}$ (or a component $X_{\mathrm{FU},i}$ without functions) is conducted according to the *compound parameterization* of the noisy max model [37, 39]. In the simple case, all of the z root causes in $\mathrm{pa}_{\mathcal{G}}(X_{\mathrm{F},i}) = \{X_{\mathrm{FC},1}, ..., X_{\mathrm{FC},z}\}$ lead to one single FM FM_x as state of $X_{\mathrm{F},i}$. Then, the occurrence of the FM is rated based on the verbal scale as "very certain", i.e., with a probability value of $98\,\%$. The remaining $2\,\%$ are distributed with $1.9\,\%$ to the state UNK and with $0.1\,\%$ to the state OK . Other possible FMs of $X_{\mathrm{F},i}$ or $X_{\mathrm{FU},i}$ are evaluated with $0\,\%$. If a node of a function includes multiple FMs FM_x as states and has multiple FCs as parent nodes $X_{FC,y}$, some of which can cause several FMs, known logical relationships and the severity of the resulting FEs are included in the determination of the parameters. We can extract from the FMECA data the information about which FCs lead to which FMs. The following example shows the parameter identification for $X_{\mathrm{F},i}$ with $Val\,(X_{\mathrm{F},i}) = \{\mathrm{FM}_1, \mathrm{FM}_2, \mathrm{UNK}, \mathrm{OK}\}$ and $\mathrm{pa}_{\mathcal{G}}(X_{\mathrm{F},i}) = \{X_{\mathrm{FC},1}, X_{\mathrm{FC},2}, X_{\mathrm{FC},3}\}$. Thereby, $X_{FC,1}$ causes the single FM FM_1 and $X_{FC,2}$ the single FM FM_2, respectively. The FC $X_{FC,3}$, on the other hand, may cause the two FMs FM_1 and FM_2. The parameters are then given by

$P(X_{F,i} \mid X_{FC,1}, \cdots X_{FC,2}, X_{FC,3})$		$X_{FC,1}$	$X_{FC,2}$	$X_{FC,3}$	
		True	True	True	Leak
$X_{F,i}$	FM_1	0.98	0.00	$\theta_{\mathrm{FM}_1 \mid \mathrm{FC}_3}$	$1e-7$
	FM_2	0.00	0.98	$\theta_{\mathrm{FM}_2 \mid \mathrm{FC}_3}$	$1e-7$
	UNK	0.019	0.019	0.019	$1e-7$
	OK	0.001	0.001	0.001	0.9999997

with

$$\begin{aligned} \theta_{\mathrm{FM}_1 \mid \mathrm{FC}_3} &= \frac{S_{max}(\mathrm{FM}_1) \cdot O_{\mathrm{FM}_1 \mid \mathrm{FC}_3}}{\sum_{x \in \{1,2\}} S_{max}(\mathrm{FM}_x) \cdot O_{\mathrm{FM_x} \mid \mathrm{FC}_3}} \cdot 0.98 \\ \theta_{\mathrm{FM}_2 \mid \mathrm{FC}_3} &= \frac{S_{max}(\mathrm{FM}_2) \cdot O_{\mathrm{FM}_2 \mid \mathrm{FC}_3}}{\sum_{x \in \{1,2\}} S_{max}(\mathrm{FM}_x) \cdot O_{\mathrm{FM_x} \mid \mathrm{FC}_3}} \cdot 0.98\,. \end{aligned} \tag{2}$$

Here, the function $S_{max}(FM_x) = \max\,\{ S_{FE_1 \mid \mathrm{FM}_x}, S_{FE_2 \mid \mathrm{FM}_x},\ \dots\ \}$ returns for FM_x as state of $X_{\mathrm{F},i}$ the largest severity from the set of severity values of the FEs that are related to FM_x in the FMECA data. Equation 2 weights the probability parameters of the FMs with regard to the maximum severity of a FE and the occurrence probability of the associated FC of an FM. These calculation rules can be applied accordingly to CPTs with any number of FMs and FCs. The leak parameters [37] are set to $1e-7 < p_O(2)$ for the states UNK and FM_x. Accordingly, the leak parameter for the state OK is set to $1 - \sum_{i \in \{\mathrm{UNK}, \mathrm{FM}_1, \mathrm{FM}_1, \dots\}} 1e-7$. These leak parameters guarantee an appropriate decision behavior with respect to the defined inference objectives. We validated and found these leak parameters in conjunction with the other probability parameters of the multi-state nodes through explorative experiments using sensitivity analyses according to Kjærulff & van der Gaag [41] and elicitation reviews [36].

3) **CPTs of FE nodes:** The CPT of a binary probability variable $X_{\mathrm{FE},i}$ of a FE is calculated for a parent node of a function $X_{\mathrm{F},f}$ (or a component $X_{\mathrm{FU},i}$) with $Val\,(X_{F,f}) = \mathrm{FM}_R \cup \mathrm{FM}_U \cup \{\mathrm{UNK}, \mathrm{OK}\}$ based on the deterministic relationships and the severity S given by the FMECA data. $\mathrm{FM}_R = \{\mathrm{FM}_{R,1}, ..., \mathrm{FM}_{R,r}\}$ is the set of the r FMs of $X_{F,f}$ that cause the FE represented by $X_{\mathrm{FE},i}$. $\mathrm{FM}_U = \{\mathrm{FM}_{U,1}, ..., \mathrm{FM}_{U,u}\}$ is the set of the u FMs of $X_{F,f}$ that do not cause this FE. The following example demonstrates the calculation of the CPT parameters of $X_{\mathrm{FE},i}$ and a corresponding parent node $X_{F,f}$ with two FMs $\mathrm{FM}_{U,1} \in \mathrm{FM}_R$ and $\mathrm{FM}_{U,1} \in \mathrm{FM}_U$:

$P\,(X_{\mathrm{FE},i} \mid X_{\mathrm{F},f})$		$X_{\mathrm{F},f}$			
		$\mathrm{FM}_{R,1}$	$\mathrm{FM}_{U,1}$	UNK	OK
$X_{\mathrm{FE},i}$	True	$\frac{S_{\mathrm{FE},i \mid \mathrm{FM}_{R,1}}}{S_{\max}(\mathrm{FM}_{R,1})}$	0.00	0.2	0.00
	False	$1 - \frac{S_{\mathrm{FE},i \mid \mathrm{FM}_{R,1}}}{S_{\max}(\mathrm{FM}_{R,1})}$	1.0	0.8	1.00

The idea of this heuristic calculation rule is: If a FM $\mathrm{FM}_{R,x} \in \mathrm{FM}_R$ comprises m FEs that are independent of the FCs, then the FE that has the highest severity $S_{\max}\,(\mathrm{FM}_{R,x})$ is to be predicted with the highest probability value, i.e., $P\,(X_{\mathrm{FE,i}} = \mathrm{True} \mid X_{\mathrm{F,f}} = S_{\max}\,(\mathrm{FM}_{R,x})) = 1.0$. The remaining $m-1$ FEs of $\mathrm{FM}_{R,x}$ should be predicted with smaller probability values with regard to the associated severity values. This calculation rule enables the determination of probability parameters of binary nodes that individually represent a Bernoulli distribution. The m binary nodes then collectively represent an overall prediction that is similar to a multi-label classification prediction. The parameters of $X_{\mathrm{FE},i}$ for the parent node configuration $X_{F,f} = \mathrm{FM}_{U,1} \in \mathrm{FM}_U$ are derived via deterministic relationships given by the FMECA, e.g., $P(X_{FE,i} = \text{False} \,|\, X_{F,f} = \text{FM}_{U,1}) = 1.0$. The parameters for $X_{F,f} = \text{UNK}$ and $X_{F,f} = \text{OK}$ are specified by domain experts via the verbal scale. Domain experts rate the scenario $P(X_{FE,i} = \text{False} \,|\, X_{F,f} = \text{UNK}) = 0.8$ as "expected" and the scenario $P(X_{FE,i} = \text{False} \,|\, X_{F,f} = \text{OK}) = 1.0$ as "absolutely certain".

4) **CPTs of CM nodes:** FMECA data does not contain any information about the frequency and success rate of applied CMs. Therefore, we define the probability parameters uniformly for the states True and False for all nodes of CMs. The probabilities of the states result from the assessments of domain experts. A node of a CM $X_{\text{CM},i}$ can comprise $1 : h$ binary parent nodes that represent FCs. If at least one parent node has the state True, then $P(X_{\text{CM},i} = \text{True} \,|\, X_{\text{FC},1} = \text{True}, ..., X_{\text{FC},h} = \text{False}) = 0.95$ ("certain"), which indicates that the corrective measure $X_{\text{CM},i}$ resolves the associated root cause $X_{\text{FC},1}$ with certainty. If all parent nodes have the state False, then a corrective measure is most certainly not required, i.e., $P(X_{\text{CM},i} = \text{False} \,|\, X_{\text{FC},1} = \text{False}, \ldots, X_{\text{FC},h} = \text{False}) = 0.98$ ("very certain"). The following example of a CPT from X_{CM} with two parent nodes illustrates this procedure:

$P(X_{\text{CM},i} \,\vert\, X_{\text{FC},u})$		True		False		$X_{\text{FC},1}$
		True	False	True	False	$X_{\text{FC},2}$
$X_{\text{CM},i}$	True	0.95	0.95	0.95	0.02	
	False	0.05	0.05	0.05	0.98	

5) **CPTs of SE nodes:** The conditional probability parameters of the nodes of functional units (X_{FU}) and structural elements (X_{SE}) are defined via deterministic relationships. If a parent node $X_{F,f}$ corresponding to a function or a component has a FM_x or is in the state UNK, the state of $X_{\text{FU},i} = \text{NOK}$. Otherwise, the state of $X_{\text{FU},i} = \text{OK}$. For a parent node $X_{F,f}$ of a node $X_{FU,i}$, the probability parameters result via these deterministic relationships to

$P(X_{\text{FU},i} \,\vert\, X_{\text{F},f})$		$X_{\text{F},f}$		
		FM_x	UNK	OK
$X_{\text{FU},i}$	OK	0	0	1
	NOK	1	1	0

The system states of $X_{FU,i}$ are propagated along all SEs of the system hierarchy according to the deterministic relationships:

$P(X_{\text{SE},i} \,\vert\, X_{\text{FU},u})$		$X_{\text{FU},u}$	
		OK	NOK
$X_{\text{SE},i}$	OK	1	0
	NOK	0	1

6) **Causal chains of FEs & FCs:** The CPT of nodes representing both FEs and FCs from different nodes of functions or components is defined as

$P(X_{\text{FE\_FC},i} \,\vert\, X_{\text{F},f})$		$X_{\text{F},f}$		
		FM_r	UNK	OK
$X_{\text{FE\_FC},i}$	True	$\frac{S_{\text{FE},i\vert\text{FM}_r}}{S_{\max}(\text{FM}_r)}$	0.2	$p_{\text{O}}(O_i)$
	False	$1 - \frac{S_{\text{FE},i\vert\text{FM}_r}}{S_{\max}(\text{FM}_r)}$	0.8	$1 - p_{\text{O}}(O_i)$

The probability parameters for $P(X_{FE\_FC,i} \,|\, X_F = \text{FM}_r)$ as well as for $P(X_{FE\_FC,i} \,|\, X_F = \text{UNK})$ match the corresponding parameters for the nodes of FEs (step 3). However, compared to the CPTs of FEs, the probability parameters $P(X_{FE\_FC,i} = \text{True} \,|\, X_F = \text{OK})$ and $P(X_{FE\_FC,i} = \text{False} \,|\, X_F = \text{OK})$ are not defined based on a qualitative expert estimation. Instead, these probability parameters are determined using the occurrence probabilities O_i of the FCs, as with the root nodes of FCs (step 1). As a result, these nodes enable adequate probabilistic reasoning along causal chains of FEs and FCs between several FMs (IO_5). We have developed this heuristic approach for parameter identification based on the presented design considerations regarding the inference objectives for FDC, the BN structure and the properties of the FMECA data. We iteratively fine-tuned the probability parameters that we initially identified via the design considerations based on empirical evaluation results. These empirical evaluation results were gained using the methods of sensitivity analyses according to Kjærulff & van der Gaag [41] and elicitation reviews [36]. In this way, we tried out several variants of parameter identification. According to domain experts, the probability parameters of the variant presented in this section led to the best results (cf. Section 6). Compared to complex BN structures and parameter identification approaches that are based solely on manual expert knowledge elicitation, our heuristic parameter identification approach for the proposed ontology-based, unified BN structure can be computed fully automatically and very efficiently (cf. Section 6.4.4).

6 Case study

We have evaluated the BDSN-FDC with a case study in the field of FDC in manufacturing. Nevertheless, our proposed approach is not limited to the considered use case and can be generally applied to any application where similar data and knowledge sources are available. In Section 6.1, we introduce the use case of the case study. Section 6.2 presents the evaluation scheme. The dataset used is described in Section 6.3. Section 6.4 contains the results and discussion. In

Section 6.5, we compare our ontology-driven BN approach to related approaches in the FDC domain and to related works. The limitations of our approach are discussed in Section 6.6.

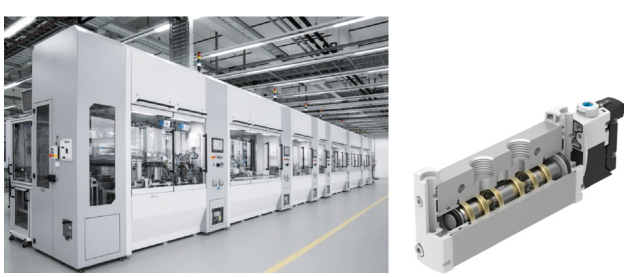
6.1 Use case

The evaluation is based on a real-world use case provided by our industry partner, Festo SE & Co. KG. It considers an automated assembly line for pneumatic solenoid valves (Fig. 5). Occurring faults have a negative impact on the technical availability, performance and quality rate of the assembly line. The use case includes two data and knowledge sources: (1) FMECAs and (2) heuristical and empirical knowledge from domain experts.

6.2 Evaluation scheme

For the BN created with FMECA data, no suitable data is available for a quantitative evaluation using statistical performance metrics. This is often the case in real-world use cases (cf. [21, 42–44]). This means that the evaluation of the BN must rely on a comparison between the decision behavior of the BN and the assessment of domain experts [22, 36, 44, 45]. In this work, we conducted such a qualitative evaluation methodology in form of a case-based test and with the assistance of two domain experts from the industrial partner. The inference objectives IO_1-IO_6 introduced in Section 3 can be uniformly evaluated with this test. In this way, we can systematically evaluate, if the prediction performance of our BN is valid for FDC.

Each sample fault case of the case-based test consists of two sets of states of the probability variables of the BN. The first set $\mathcal{E}$ includes the states of the variables of the BN which correspond to observed events or conditions such as the presence or absence of fault effects or root causes. The second set $\mathcal{X}$ contains the states of hypothesis probability variables that, according to the assessment of experts, correspond to the expected model predictions for the given fault case. For each sample fault case, the states of the probability variables from the set $\mathcal{E}$ are entered into the BN as evidence. Subsequently,



(a) (b)

Fig. 5 Assembly of pneumatic solenoid valves. **a**) Assembly line. **b**) Cross-section of the valve

we check whether the resulting model prediction, represented by the posterior probability distribution of the BN, are consistent with the expected set of hypothesis variable states $\mathcal{X}$. If the model prediction matches the expected set of states, the prediction is rated as correct (✓); otherwise, as incorrect (✗). The success rate ratio

$$\text{Success Rate} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \tag{3}$$

expresses the proportion of correct predictions in relation to the total number of predictions.

In order to rate the model predictions to be correct or incorrect, the predicted continuous-valued probabilities of the posterior distribution must be transformed to discrete decisions about predicted variable states. For multi-state nodes, a model prediction is considered correct if the state of the variable with the highest predicted probability matches the expected state of the variable in $\mathcal{X}$. For a node X_i with binary states, the predicted probability values are transformed to the binary decision about the predicted variable state by applying the simple threshold

$$X_i = \begin{cases} \text{True}\ , & \text{if } P(X_i = \text{True} \,|\, \mathcal{E}) \geq 0.5 \\ \text{False}\ , & \text{else} \end{cases} . \tag{4}$$

For a group of binary nodes of the same type (e.g., multiple nodes of FEs belonging to one node of a function), exactly the variable with its state according to Eq. 4 is predicted whose probability value is the highest predicted value among the same states of the variables of the respective group of nodes. We demonstrate this evaluation methodology with two sample fault cases in Section 6.4.

6.3 Dataset

The case-based test comprises a set of $N = 20$ sample fault cases. The Table 7 in the appendix of this paper summarize these 20 sample fault cases and the associated evaluation results. For each of the 20 sample fault cases in the Table 7, we indicate the inference runtime of the BN. We selected the sample fault cases with respect to the inference objectives IO_1-IO_6. Moreover, our sample fault cases comprise edge cases for which either a particularly clear or a complex decision behavior of the BN is to be expected. Five of the 20 sample fault cases allow the simultaneous testing of two inference objectives. This results in a total of 25 test cases. The BN created for the evaluation and the used FMECA data as well as the sample fault cases of the case-based test are publicly available as supplementary material on GitHub[4].

[4] BDSN-FDC (https://github.com/IPVS-AS/BDSN-FDC)

Table 2 First sample fault case (no. 3 in Table 7)

Inference objective	IO_1
Set of evidence $\mathcal{E}$	{F03 = FM03,FC04 = False}
Hypothesis set $\mathcal{X}$	{FC06 = True, FC07 = False,
	FC08 = False}
Posterior	$P(\text{FC05} = \text{True} \mid \mathcal{E}) = 0.0901$
distribution for $\mathcal{E}$	$P(\text{FC06} = \text{True} \mid \mathcal{E}) = \mathbf{0.9007}$
	$P(\text{FC07} = \text{True} \mid \mathcal{E}) = \mathbf{0.0021}$
	$P(\text{FC08} = \text{True} \mid \mathcal{E}) = \mathbf{0.00}$
Fulfillment	✓

6.4 Results & discussion

We use two sample fault cases to demonstrate the inference mechanisms of the developed BN and the evaluation methodology in the following two subsections. Afterwards, the overall evaluation results based on all 20 sample fault cases are presented in Section 6.4.3. In Section 6.4.4, the computational performance of our approach is evaluated. In contrast to related works, the evaluation of our BN approach is much more comprehensive and involves a case base with 25 test cases across six inference objectives. Thereby, each inference objective is evaluated using two to seven sample fault cases (cf. Table 4). The evaluation procedures used in related works [21–23, 45] are purely qualitative and limited to case studies with a maximum of one or two sample fault cases. In this way, related works only evaluate their approaches for one or two inference objectives. Some of our inference objectives, e.g., the derivation of suitable corrective measures (IO_3) or the localization of fault root causes in complex manufacturing settings (IO_6), are not even investigated by related works, since their proposed BNs do not model these causal relationships (cf. Section 6.5.2).

We conducted all experiments on a computer with an Intel i7-11800H@2.30 GHz processor and 32 GB RAM. We used the exact inference algorithm *Clustering* from the software *SMILE* for inference with the BN.

6.4.1 Sample fault case 1

Table 2 shows the sample fault case 1. The set of evidence $\mathcal{E}$ is entered into the BN. The domain experts expect *FC06* to be True for the given set of evidence and that the root causes *FC*07 and *FC*08 cannot result in the failure mode FM03 of the function *F03* (cf. hypothesis set $\mathcal{X}$).

Figure 6 depicts the posterior probability distribution for $\mathcal{E} = \{\text{F03} = \text{FM03}, \text{FC04} = \text{False}\}$ of the part of the BN that is relevant for the evaluation with respect to IO_1 and the associated hypothesis set $\mathcal{X}$. The posterior probability distribution of the BN is rated as correct, since the expected result, given by $\mathcal{X}$, can be inferred with Eq. 4 based on the predicted probabilities for the respective states of the nodes FC06, FC07, FC08: $P(\text{FC06} = \text{True} \mid \mathcal{E}) = 0.9007 \geq 0.5$, $P(\text{FC07} = \text{True} \mid \mathcal{E}) = 0.0021 < 0.5$ and $P(\text{FC08} = \text{True} \mid \mathcal{E}) = 0.0000 < 0.5$. The hypothesis set $\mathcal{X}$ includes no outcome of the state of the node FC05. Hence, to correctly validate the decision behavior of the BN, we must ensure that the predicted probability value of $P(\text{FC06} = \text{True} \mid \mathcal{E}) = 0.9007$ is the largest predicted value among all states True of the nodes of all *FCs* (cf. Section 6.2). For the first sample fault case, $P(\text{FC06} = \text{True} \mid \mathcal{E}) > P(\text{FC05} = \text{True} \mid \mathcal{E})$ holds (cf. Table 2 and Fig. 6). This means that the BN successfully predicted the most probable root cause *FC06* for the identified failure mode FM03 of the function F03 and the excluded root cause *FC*04 (IO_1).

To validate the robustness of the BN's decision behavior with respect to the identified probability parameters, we conducted a sensitivity analysis for this sample fault case. The details and the result of this sensitivity analysis are reported in C of the appendix. The obtained result shows that the BN only has small reachable probability ranges of the different target node states for a change of $\pm 10\,\%$ in the influencing parameters. We conclude that the identified probability parameters lead to clear decisions that are robust to changes in the underlying parameters.

6.4.2 Sample fault case 2

The evaluation of the BN with the sample fault case 2 (cf. Table 3) is conducted analogously. The second fault case aims to evaluate the traceability of causal chains between multiple faults.

The posterior probability distribution of the part of the BN for $\mathcal{E} = \{\text{F01} = \text{FM01}\}$ is shown in Fig. 7. The BN structure in Fig. 7 shows the causal chain $\text{FC02} \leftarrow \text{F01} \rightarrow \text{FE03\_FC07} \rightarrow \text{F03} \rightarrow \text{FE07}$ that is expected for $\mathcal{E}$ by the domain experts. Thereby, the node *FE03_FC07* is expected to fulfill two roles: (1) the fault effect of FM01 of *F01* and (2) the root cause of FM04 of *F03*. The posterior probability distribution of the BN is considered as correct because it matches the expected states of the probability variables in $\mathcal{X}$: The BN predicts the correct root cause for the node *F01*, since $P(\text{FC02} = \text{True} \mid \mathcal{E}) = 0.9083 \geq 0.5$ and $P(\text{FC02} = \text{True} \mid \mathcal{E}) > P(\text{FC01} = \text{True} \mid \mathcal{E})$ (cf. Table 3 and Fig. 7). The following fault effect *FE03_FC07* is clearly predicted as True with a probability of 1.0. Subsequently, the node *FE03_FC07* causes the correct failure mode state FM04 of the node *F03*. This can be inferred from the posterior probabilities, as outlined in Section 6.2, since $P(\text{F03} = \text{FM04} \mid \mathcal{E}) = 0.9797$, which is the highest among all posterior probabilities for the possible states $S = \{\text{FM03}, \text{FM04}, \text{UNK}, \text{OK}\}$ of *F03*:

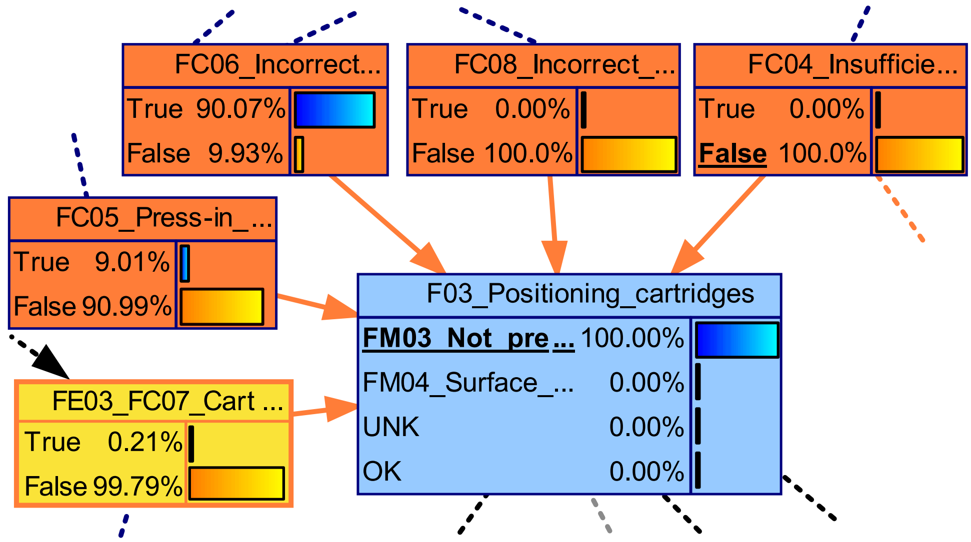


Fig. 6 Posterior probability distribution of the respective BN nodes for the sample fault case 1

Table 3 Second sample fault case (no. 17 in Table 7)

Inference objective	IO_5
Set of evidence $\mathcal{E}$	$\{F01 = FM01\}$
Hypothesis set $\mathcal{X}$	$\{FC02 = True,$
	$FE03\_FC07 = True,$
	$F03 = FM04, FE07 = True\}$
Posterior	$P(FC01 = \mathrm{True} \mid \mathcal{E}) = 0.0908$
distribution for $\mathcal{E}$	$P(FC02 = \mathrm{True} \mid \mathcal{E}) = \mathbf{0.9083}$
	$P(FE03\_FC07 = \mathrm{True} \mid \mathcal{E}) = \mathbf{1.0}$
	$P(F03 = FM03 \mid \mathcal{E}) = 0.0003$
	$P(F03 = FM04 \mid \mathcal{E}) = \mathbf{0.9797}$
	$P(FE05 = \mathrm{True} \mid \mathcal{E}) = 0.0041$
	$P(FE06 = \mathrm{True} \mid \mathcal{E}) = 0.0043$
	$P(FE07 = \mathrm{True} \mid \mathcal{E}) = \mathbf{0.9838}$
Fulfillment	✓

$$P(F03 = \mathrm{FM04} \mid \mathcal{E}) = \max_{x \in S} P(F03 = x \mid \mathcal{E}) \quad .$$

The predicted failure effect for FM04 of *F03* is *FE07* because $P(\mathrm{FE07} = \mathrm{True} \mid \mathcal{E}) = 0.9838$ and $P(\mathrm{FE07} = \mathrm{True} \mid \mathcal{E}) > P(\mathrm{FE06} = \mathrm{True} \mid \mathcal{E}) > P(\mathrm{FE05} = \mathrm{True} \mid \mathcal{E})$. We conclude that the multivariate probability distribution represented by the developed BN enables correct reasoning along the fault chain given by the second sample fault case.

We also validated the robustness of the BN's decision behavior with respect to the identified probability parameters via a sensitivity analysis for this second sample fault case. The details and the result of this sensitivity analysis are reported in Section 10 of the appendix. As for the first sample fault case, the obtained result demonstrates a very robust decision behavior of the BN to changes of $\pm 10\,\%$ in the influencing parameters.

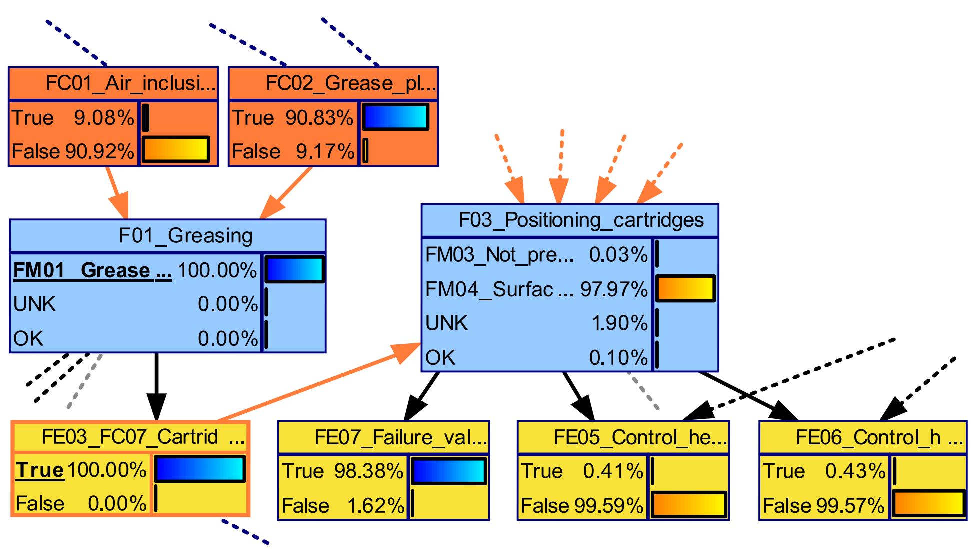


Fig. 7 Posterior probability distribution of the respective BN nodes for the sample fault case 2

6.4.3 Overall evaluation results

Table 4 summarizes the success rates of the BN for each of the six inference objectives IO_1-IO_6 and for the total number of sample fault cases. For all sample fault cases and along all six inference targets, the predictions of the BN correspond to the expected results, i.e., the overall prediction performance of the BN achieves a success rate of 25/25. These results verify that the fault knowledge extracted from FMECA data can be successfully utilized for FDC. The proposed heuristic approach for parameter identification ensures that an appropriate set of probability parameters is found that enables accurate reasoning with the fault knowledge represented by the BN structure.

The developed BN supports predictive and diagnostic inference mechanisms via its causal network structure for FDC. The inference mechanism of explaining away [36, 46] may be used to support inter-causal reasoning by identifying and narrowing down the root causes of a detected fault effect. Through the causal network structure, maintenance personnel can intuitively understand the decision behavior of the BN and derive additional fault knowledge for their tasks, such as causal fault chains or the location of root causes.

6.4.4 Computational performance analysis

In order to analyze the computational performance of our proposed approach, we calculated the computational runtimes of the three core components: (i) the automated ontology-driven generation of the BN structure, (ii) the heuristic parameter identification approach based on the considered dataset and (iii) the mean inference time of the BN for all 20 sample fault cases. Each runtime measurement was repeated 100 times to ensure statistical robustness. We report the mean and standard deviation (SD) of the runtimes, and additionally compute non-parametric 95 % bootstrap confidence intervals (95 % CI, $n = 10\,000$) to quantify uncertainty around the mean estimates of the runtimes [47]. The results are summarized in Table 5. The measured runtimes demonstrate that the proposed approach is computationally efficient and scalable.

The BN structure creation and parameter identification steps complete in less than $130\,ms$ combined. The creation of the BN structure can be efficiently computed in $49.7348\,ms$ due to the clearly structured and template-based creation schema defined by the ontology. The heuristic parameter identification approach completes in $75.8547\,ms$. Compared to iterative parameter learning approaches, e.g., using the EM algorithm, which typically report training times in the order of seconds to minutes, the reported runtime for our approach is remarkably low. This observed efficiency is primarily due to two design choices. First, our parameter identification approach is based on heuristic mathematical equations, expert knowledge formulated as static rules and deterministic relationships. This way, our parameter identification approach can be efficiently computed within in one iteration. Second, the modeling of multi-state nodes using noisy-max nodes, which scale linearly with the number of parent nodes, reduces the parameter space and computational overhead significantly. Given that each fault instance can be processed independently, further performance improvements may still be feasible through parallelization of the steps required by the algorithm for the BN structure generation and the steps of the heuristic parameter identification algorithm.

The mean inference time per fault case is $0.0187\,ms$. The inference step can be computed efficiently due to the relatively shallow parts of the BN that represent fault instances. In this way, the evidence of an inference objective that is entered into the BN must not be propagated along complex network structures, but only for a few nodes.

Our dataset is still representative for large-scale and more complex systems, where only the number of FMECA instances would increase. The size of each single fault instance modeled by the BN would be only slightly different. Each individual fault instance would be still represented by a multi-state node of the respective function or component involving approximately 3-8 states as well as approximately 1-10 FE child nodes, 1-10 FC parent nodes and 1-10 CM nodes. This means that the modeling complexity of the BN stays constant with an increasing number of integrated fault instances.

In addition to runtime efficiency, our approach offers high maintainability in large-scale systems. The structure of the BN defined by the ontology can be incrementally updated if new fault instances are available. The heuristic parameter identification also enables an incremental and efficient update

Table 4 Summary of the results of the case-based test grouped by IO_1-IO_6

IO_x	Number of test cases	Success rate
IO_1	4	4/4
IO_2	7	7/7
IO_3	4	4/4
IO_4	6	6/6
IO_5	2	2/2
IO_6	2	2/2
$\sum$	**25**	$\mathbf{25/25}$

Table 5 Computational performance analysis

	Mean Runtime ± SD [95% CI]95
Creation of the BN structure	49.7348 ± 1.2098 [49.5043; 49.9755]
Heuristic parameter identification	75.8547 ± 1.5577 [75.5535; 76.16368]
Inference time (mean of all 20 fault cases)	0.0187 ± 0.0009 [0.0184; 0.0188]

All values in milliseconds (ms)

of the probability parameters of newly added fault instances and the interlinked deterministic nodes of system elements.

6.5 Comparison to related work

In the following Section 6.5.1, we compare the proposed approach to related approaches in the FDC domain in general. Subsequently, Section 6.5.2 specifically summarizes related work on BN approaches.

6.5.1 Common FDC methods

To assess the unique value of our ontology-driven BN approach, Table 6 provides a qualitative comparison with commonly used alternative solution approaches. These include search and query systems, rule-based and case-based reasoning systems, machine learning classifiers, large language models (LLMs) with retrieval-augmented generation (RAG) techniques, and approaches based on frequent itemset mining [4, 8, 13, 15, 16]. The evaluation is based on seven criteria that are relevant for FDC in manufacturing. We have selected these criteria because they are suitable for a qualitative comparison of the different methods and underscore the unique value of our approach.

Search and query systems rely on relational databases and return flat lists of results. While they scale reasonably well, they lack automated reasoning capabilities. The user must draw her/his own conclusions based on the query results retrieved.

Rule-based and case-based systems offer a discrete decision behavior and strong knowledge integration capabilities. However, they are limited in handling uncertainty. Such systems are difficult to scale because they are based on an extensive rule or case base that must be elaborately created [4, 13].

Classifiers such as decision trees are efficient for discrete predictions. However, they require labeled datasets and only provide limited explainability and weak integration of domain knowledge. Hence, classical classifiers cannot be applied to typical FMECA data, as this data does not contain statistical distributions about the occurrence of fault cases. Moreover, one classifier cannot fulfill multiple different inference objectives. This means, to support multiple different inference objectives, as defined in this work, multiple classifiers must be created, each specialized for a specific inference objective.

LLMs (with RAG techniques) demonstrate strong scalability and generalizability, and they can flexibly answer text-based queries [15, 16]. However, they lack causal reasoning, provide limited transparency, and their outputs are not guaranteed to be consistent or verifiable in safety-critical contexts.

Frequent itemset mining can uncover associations in data and partially support explainability, but it does not capture causal dependencies and cannot reason under uncertainty.

In recent years, ontology-based systems for domain knowledge representation and automatic reasoning have become an important topic to improve the efficiency and effectiveness of FDC [1, 8]. **Semantic web technologies**, besides BN approaches, are commonly used to leverage ontology-based knowledge models [1, 8]. A key advantage

Table 6 Qualitative evaluation of our ontology-driven BN approach in comparison to related approaches to FDC

	Search & Query	Rule-based / Case-based	Classifiers (e.g., Decision Trees)	LLMs, RAG	Frequent Itemset Mining	Semantic Web Technologies	**This work**
Required data	Relational database	Rule base / case base	Frequency-based, labeled dataset	Prompting templates and embedding databases	Frequency-based dataset	Rule base, ontology-based	FMECA structure, ontology-based
Reasoning mechanism	None	Rule-based, case-based reasoning	Class predictions	Text generation question answering	Association rules	Rule-based reasoning	Causal, probabilistic reasoning
Decision behavior	Flat list	Static, discrete	Discrete	Versatile, text-based	Frequent pattern-based	Static, discrete	Probabilistic, considering uncertainties
Explainability of Inference	○	◑	◔	○	◑	◑	●
Knowledge integration	○	◕	◔	◕	◔	◕	●
Scalability	◑	○	◔	◕	◑	◑	◕
Generalizability	◕	◔	◑	●	◑	◑	◕

Fulfillment of criteria: ● fully, ◕ almost fully, ◑ half, ◔ partially, ○ not of semantic web technologies is that ontologies are part of the methodological approach and implementation of knowledge bases, inference mechanisms and knowledge querying. Semantic web technologies support the modeling of complex ontology-based knowledge models. However, the almost unlimited possibilities for knowledge modeling with ontologies often lead to application-specific knowledge models that have poor generalizability and that complicate the automated creation of the knowledge base. Semantic web technologies are typically based on a rule base and enable a static, discrete decision behavior.

In contrast, **the proposed ontology-driven BN approach** combines causal and probabilistic reasoning with structured domain knowledge, e.g., originating from FMECAs. The DAG of the BN represents causal relationships and is characterized by simplicity and naturalness in the representation of knowledge. This facilitates the explainability of the decision-making process [17, 31]. Our approach supports decision-making taking uncertainties into account. Although our approach cannot be generalized and applied to different domains without restriction, it can be easily transferred within FDC applications and to similar data and knowledge sources in manufacturing. Our approach has strong scalability capabilities due to its very efficient computational performance (cf. Section 6.4.4) and the ontology-driven generation of the BN.

6.5.2 Bayesian network approaches

Several works pursue approaches for the creation of BNs based on FMECA data [19–23, 38, 42, 48, 49]. Some works use fault trees as an additional knowledge source [19, 24, 25, 38, 48]. Among these related works, Yang et al. [19], Lian et al. [20], Ma et al. [38], García & Gilabert [21] and Brahim et al. [22] model the cause-effect relationships that are typical for FMECAs, i.e., consisting of FCs → FMs → FEs, explicitly in the BN structure. The related works mentioned present application-specific, isolated BN approaches that are mainly developed for fault diagnosis and root cause analysis. CMs are not explicitly modeled in the BN structure. Hence, approaches supporting fault correction only exist in a broader sense, if measures can be derived implicitly from decision recommendations regarding root causes.

All related works use expert knowledge to identify the probability parameters leading to expected inference results. Only the studies by García & Gilabert [21], Brahim et al. [22] and Kirchhoff et al. [23] take into account additional prior information from available data and knowledge sources, such as criticality information from FMECAs. However, these studies only use little prior information and individual parameters of the criticality information available in the FMECA data, e.g., only the occurrence probability O.

The related works integrate the fault knowledge originating from only one or two data or knowledge sources. A drawback of the related works is that they directly create the BN structure using the underlying data sources. This is typically an elaborate task, since every data source, even if they include the same type of fault knowledge, must be manually integrated into a BN. These approaches to creating the BN structure are difficult to transfer to other applications and data sources. Here, ontologies can be used to simplify and accelerate the creation of BNs [44]. Several related studies [45, 50–53] consider the modeling of domain knowledge via ontologies to be simpler and more efficient than the direct modeling of knowledge via BNs. In addition, the creation of BNs can be partially automated using ontologies [45]. Ding et al. [52] and Fenz [53] even utilize value constraints and semantic relations that are additionally defined by ontologies for the identification of the BN parameters. In the field of quality-related fault diagnosis of manufacturing systems, Sayed & Lohse [45] use an ontology-based domain model and fault information from FMEAs for the semi-automated creation of a BN. This domain model describes the product-process-resource relationships. The probability parameters of the created BN are determined exclusively via expert knowledge, i.e., the BN structure is created regardless of the parameter identification. The existing approaches for deriving BNs from ontologies are still very specialized and application-specific. Furthermore, existing ontologies are mostly limited to a single data or knowledge source.

6.6 Limitations

The proposed parameter identification approach using FMECA data is subject to some limitations. Firstly, FMECAs generally have limitations in capturing complex fault scenarios such as interdependencies between several FMs, FCs and FEs. Secondly, FMECAs only support a limited quantitative risk and criticality analysis, e.g., via the RPN (cf. Section 2.2) [11, 30]. Thirdly, FMECAs and expert knowledge are partly based on heuristic and qualitative assumptions. Furthermore, FMECA data is usually not updated with empirical findings obtained in the field. Therefore, the proposed heuristic parameter identification approach cannot guarantee that the derived parameters of the BN result in a probability distribution that precisely reflects the actual probability distribution of fault scenarios in the considered problem domain. The case-based evaluation conducted does also not allow to draw any conclusions about actual probability distributions. Hence, part of future work is to evaluate the decision behavior of the BN via field tests of the BDSN-FDC.

We conclude that the proposed heuristic approach for parameter identification is suitable for the first initialization of the parameters after the BN structure has been created.

When using the BN in production, users must assess the predictive quality of its decisions.

Our proposed ontology-driven approach allows to integrate the fault knowledge contained in empirically gained datasets that represent the actual statistical distribution of the occurrences of fault cases, e.g., historical logs of historic maintenance and repair tasks. Once sufficient historic maintenance data is available for a function or component, we can learn the respective probability parameters of the associated fault instance modeled by the BN via a parameter learning algorithm, e.g., via the expectation maximization (EM) algorithm [54]. In this way, we can adjust the initial probability parameters identified using the FMECA data by probability parameters learned via a parameter learning algorithm. These new probability parameters reflect the observed actual frequencies of fault events. The criterion, if sufficient historic maintenance data is available for a function or component, depends on the number of faults that have actually occurred. If the number of occurred fault cases belonging to a function or component n_{Faults} is greater than a threshold η (e.g., 10), the parameter learning procedure can start. In a follow-up paper, we are going to present a novel guided parameter learning approach based on the EM algorithm and historic maintenance data that integrates prior knowledge to learn valid probability parameters for the BN as described above.

As another part of future work, the empirical insights gained over time in production, including information on occurred faults and user experiences, may be incorporated into the decision support system in the form of user feedback (cf. Section 3.5). Based on the provided user feedback, the probability parameters of the BN may be adapted with respect to the desired decision behavior expected by the user. In this way, the decision behavior of the BN can be improved based on novel empirical insights. We envision two user feedback integration approaches. The first approach utilizes an intuitive graphical user interface that enables users to directly adjust the probability parameters via sliders. This knowledge-based approach is similar to the offerings of common BN software tools such as GeNIe (cf. Section 3.6). The second approach does not require users to have profound statistical knowledge. It enables the parameter adaption in an incremental way using data sampling and parameter learning techniques.

7 Conclusion

In this paper, we present the BDSN-FDC, a novel ontology-driven BN approach for decision support to FDC in manufacturing. We developed a generic ontology that models fault knowledge from numerous data and knowledge sources available in manufacturing, such as FMECA data. This ontology is used to build the causal structure of BNs intended to analyze faults and to derive corrective measures. We propose a novel heuristic parameter identification approach that leverages prior information and deterministic relationships from FMECA data, as well as expert knowledge. We evaluated the BDSN-FDC via a case-based test. The results show that the BN enables accurate predictions for predictive and diagnostic user queries with a success rate of $100\,\%$. By using the BDSN-FDC, maintenance personnel can execute their FDC tasks more efficiently and discover previously unknown fault knowledge. Our proposed approach is largely application-independent. It can be easily applied to any application where similar data and knowledge sources are available.

Appendix A Verbal scale

Figure 8 shows the verbal scale used within in this work to map verbal probabilistic terms to probability values.

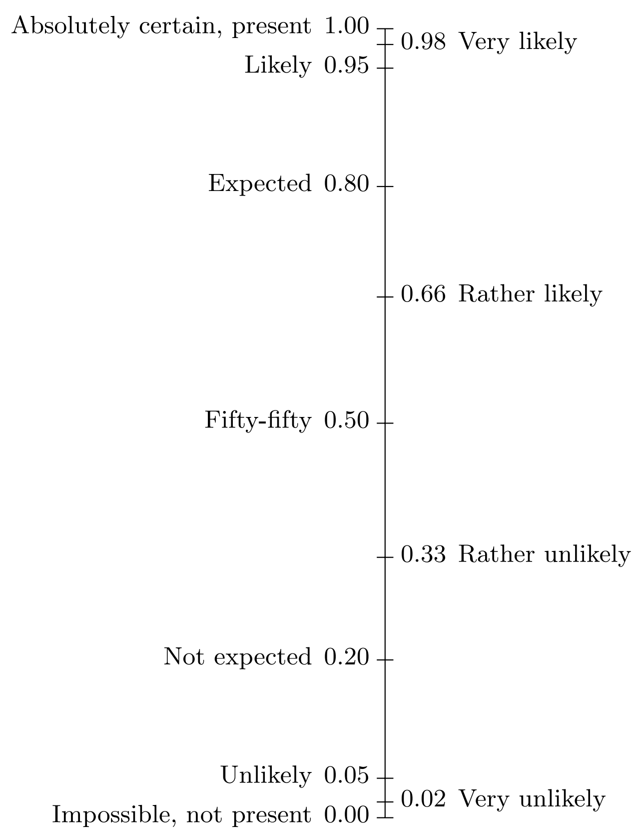


Fig. 8 Mapping of verbal probabilistic terms to probability values

Appendix B Sample fault cases

The sample fault cases of the case-based test and the corresponding posterior probability distributions of the BN are summarized in the Table 7. The posterior probabilities of the probability variables are highlighted in bold if the predicted probability values match the states of the hypothesis variables expected by two domain experts.

Table 7 Sample fault cases of the case-based test

Case No.	IO	Set of evidence $\mathcal{E}$	Hypothesis set $\mathcal{X}$	Inference time	Predicted posteriori distribution for $\mathcal{E}$	Fulfillment
1	IO_1	$\{F01=FM01\}$	$\{FC02=True\}$	0.0170 ± 0.0048	$P(FC01 = True \mid \mathcal{E}) = 0.0908$ $P(FC02 = True \mid \mathcal{E}) = \mathbf{0.9083}$	✓
2	IO_1, IO_3	$\{F02=FM02\}$	$\{FC04=True,$ $CM06=True\}$	0.0166 ± 0.0019	$P(FC03 = True \mid \mathcal{E}) = 0.0196$ $P(FC04 = True \mid \mathcal{E}) = \mathbf{0.9802}$ $P(CM04 = True \mid \mathcal{E}) = 0.0382$ $P(CM05 = True \mid \mathcal{E}) = 0.0382$ $P(CM06 = True \mid \mathcal{E}) = \mathbf{0.9316}$	✓
3	IO_1	$\{F03=FM03,$ $FC04=False\}$	$\{FC06=True,$ $FC07=False,$ $FC08=False\}$	0.0180 ± 0.0010	$P(FC05 = True \mid \mathcal{E}) = 0.0901$ $P(FC06 = True \mid \mathcal{E}) = \mathbf{0.9007}$ $P(FC07 = True \mid \mathcal{E}) = \mathbf{0.0021}$ $P(FC08 = True \mid \mathcal{E}) = \mathbf{0.00}$	✓
4	IO_1, IO_3	$\{F03=FM04\}$	$\{FC07=True,$ $FC05=False,$ $FC06=False,$ $CM08=True\}$	0.0183 ± 0.0014	$P(FC04 = True \mid \mathcal{E}) = 0.1000$ $P(FC05 = True \mid \mathcal{E}) = \mathbf{0.0}$ $P(FC06 = True \mid \mathcal{E}) = \mathbf{0.0}$ $P(FC07 = True \mid \mathcal{E}) = \mathbf{0.8959}$ $P(FC08 = True \mid \mathcal{E}) = 0.0042$ $P(CM08 = True \mid \mathcal{E}) = \mathbf{0.8532}$	✓
5	IO_2	$\{FC01=True\}$	$\{F01=FM01,$ $FE03=True\}$	0.0220 ± 0.0034	$P(F01 = FM01 \mid \mathcal{E}) = \mathbf{0.9799}$ $P(FE01 = True \mid \mathcal{E}) = 0.7038$ $P(FE02 = True \mid \mathcal{E}) = 0.7038$ $P(FE03 = True \mid \mathcal{E}) = \mathbf{0.9837}$	✓
6	IO_2	$\{FC04=True\}$	$\{F02=FM02,$ $FE06=True\}$	0.0181 ± 0.0011	$P(F02 = FM02 \mid \mathcal{E}) = \mathbf{0.9800}$ $P(FE04 = True \mid \mathcal{E}) = 0.7660$ $P(FE05 = True \mid \mathcal{E}) = 0.6802$ $P(FE06 = True \mid \mathcal{E}) = \mathbf{0.9923}$	✓
7	IO_2	$\{FC04=True\}$	$\{F03=FM03,$ $FE06=True\}$	0.0171 ± 0.0012	$P(F03 = FM03 \mid \mathcal{E}) = \mathbf{0.5188}$ $P(F03 = FM04 \mid \mathcal{E}) = 0.4612$ $P(FE05 = True \mid \mathcal{E}) = 0.6802$ $P(FE06 = True \mid \mathcal{E}) = \mathbf{0.9923}$ $P(FE07 = True \mid \mathcal{E}) = 0.9262$	✓
8	IO_2	$\{FC05=True\}$	$\{F03=FM03,$ $FE06=True\}$	0.0204 ± 0.0014	$P(F03 = FM03 \mid \mathcal{E}) = \mathbf{0.9800}$ $P(F03 = FM04 \mid \mathcal{E}) = 0.0000$ $P(FE05 = True \mid \mathcal{E}) = 0.5484$ $P(FE06 = True \mid \mathcal{E}) = \mathbf{0.9838}$ $P(FE07 = True \mid \mathcal{E}) = 0.8749$	✓

Table 7 (continued)

Case No.	IO	Set of evidence $\mathcal{E}$	Hypothesis set $\mathcal{X}$	Inference time	Predicted posteriori distribution for $\mathcal{E}$	Fulfillment
9	IO_2, IO_3	$\{FC08 = True\}$	$\{F03 = FM04,$ $FE07 = True,$ $CM07 = True\}$	0.0199 ± 0.0011	$P(F03 = FM03 \mid \mathcal{E}) = 0.0003$ $P(F03 = FM04 \mid \mathcal{E}) = \mathbf{0.9798}$ $P(FE05 = True \mid \mathcal{E}) = 0.0041$ $P(FE06 = True \mid \mathcal{E}) = 0.0043$ $P(FE07 = True \mid \mathcal{E}) = \mathbf{0.9838}$ $P(CM07 = True \mid \mathcal{E}) = \mathbf{0.9500}$	✓
10	IO_2, IO_4	$\{FC03 = True,$ $FE05 = True\}$	$\{F02 = FM02,$ $F03 = OK\}$	0.01884 ± 0.0010	$P(F02 = FM02 \mid \mathcal{E}) = \mathbf{0.9931}$ $P(F03 = OK \mid \mathcal{E}) = \mathbf{0.9972}$	✓
11	IO_2, IO_4	$\{FC05 = True,$ $FE07 = True\}$	$\{F02 = OK,$ $F03 = FM03\}$	0.0203 ± 0.0016	$P(F02 = OK \mid \mathcal{E}) = \mathbf{0.9995}$ $P(F03 = FM03 \mid \mathcal{E}) = \mathbf{0.9956}$	✓
12	IO_3	$\{FC06 = True\}$	$\{CM04 = True,$ $CM05 = True\}$	0.0185 ± 0.0012	$P(CM04 = True \mid \mathcal{E}) = \mathbf{0.9500}$ $P(CM05 = True \mid \mathcal{E}) = \mathbf{0.9500}$	✓
13	IO_4	$\{FE01 = True\}$	$\{F01 = FM01,$	0.0206 ± 0.0011	$P(F01 = FM01 \mid \mathcal{E}) = \mathbf{0.9943}$ $P(FC01 = True \mid \mathcal{E}) = 0.0908$ $P(FC02 = True \mid \mathcal{E}) = \mathbf{0.9080}$	✓
14	IO_4	$\{FE05 = True,$ $F02 = UNK\}$	$\{F03 = FM03,$ $FC04 = True\}$	0.0172 ± 0.0009	$P(F03 = FM03 \mid \mathcal{E}) = \mathbf{0.7604}$ $P(F03 = FM04 \mid \mathcal{E}) = 0.2098$ $P(FC04 = True \mid \mathcal{E}) = \mathbf{0.9861}$ $P(FC05 = True \mid \mathcal{E}) = 0.0$ $P(FC06 = True \mid \mathcal{E}) = 0.0$	✓
15	IO_4	$\{FE04 = True,$ $FC04 = False\}$	$\{F02 = FM02,$ $FC03 = True\}$	0.01804 ± 0.0009	$P(F02 = FM02 \mid \mathcal{E}) = \mathbf{0.9925}$ $P(FC03 = True \mid \mathcal{E}) = \mathbf{0.9874}$	✓
16	IO_4	$\{FE06 = True,$ $FC04 = False,$ $FC07 = False,$ $FC08 = False\}$	$\{F03 = FM03,$ $FC06 = True\}$	0.0192 ± 0.0039	$P(F02 = FM03 \mid \mathcal{E}) = \mathbf{0.9835}$ $P(F02 = FM04 \mid \mathcal{E}) = 0.0102$ $P(FC05 = True \mid \mathcal{E}) = 0.0890$ $P(FC06 = True \mid \mathcal{E}) = \mathbf{0.8898}$	✓
17	IO_5	$\{F01 = FM01\}$	$\{FC02 = True,$ $FE03\_FC07 = True$ $F03 = FM04,$ $FE07 = True\}$	0.0177 ± 0.0019	$P(FC01 = True \mid \mathcal{E}) = 0.0908$ $P(FC02 = True \mid \mathcal{E}) = \mathbf{0.9083}$ $P(FE03\_FC07 = True \mid \mathcal{E}) = \mathbf{1.0}$ $P(F03 = FM03 \mid \mathcal{E}) = 0.0003$ $P(F03 = FM04 \mid \mathcal{E}) = \mathbf{0.9797}$ $P(FE05 = True \mid \mathcal{E}) = 0.0041$ $P(FE06 = True \mid \mathcal{E}) = 0.0043$ $P(FE07 = True \mid \mathcal{E}) = \mathbf{0.9838}$	✓

Table 7 (continued)

Case No.	IO	Set of evidence $\mathcal{E}$	Hypothesis set $\mathcal{X}$	Inference time	Predicted posteriori distribution for $\mathcal{E}$	Fulfillment
18	IO_5	{F02 = FM02}	{FE06 = True, F03 = FM03, FC04 = True}	0.0170 ± 0.0014	$P(\mathrm{F03}=\mathrm{FM03}\,\vert\,\mathcal{E})=$ **0.5086**	✓
					$P(\mathrm{F03}=\mathrm{FM04}\,\vert\,\mathcal{E})=0.4521$	
					$P(\mathrm{FE04}=\mathrm{True}\,\vert\,\mathcal{E})=0.7778$	
					$P(\mathrm{FE05}=\mathrm{True}\,\vert\,\mathcal{E})=0.6828$	
					$P(\mathrm{FE06}=\mathrm{True}\,\vert\,\mathcal{E})=$ **1.0**	
					$P(\mathrm{FE07}=\mathrm{True}\,\vert\,\mathcal{E})=0.9079$	
					$P(\mathrm{FC03}=\mathrm{True}\,\vert\,\mathcal{E})=0.0196$	
					$P(\mathrm{FC04}=\mathrm{True}\,\vert\,\mathcal{E})=$ **0.9802**	
					$P(\mathrm{FC05}=\mathrm{True}\,\vert\,\mathcal{E})=0.0$	
					$P(\mathrm{FC06}=\mathrm{True}\,\vert\,\mathcal{E})=0.0$	
					$P(\mathrm{FE03\_FC07}=\mathrm{True}\,\vert\,\mathcal{E})=0.0021$	
					$P(\mathrm{FC08}=\mathrm{True}\,\vert\,\mathcal{E})=0.0$	
19	IO_6	{F01 = FM01, F03 = OK}	{FU01 = NOK, FU02 = OK, SE01 = NOK, SE02 = NOK, SE03 = NOK, SE04 = OK}	0.0173 ± 0.0009	$P(\mathrm{FU01}=\mathrm{NOK}\,\vert\,\mathcal{E})=$ **1.0**	✓
					$P(\mathrm{FU02}=\mathrm{OK}\,\vert\,\mathcal{E})=$ **1.0**	
					$P(\mathrm{SE01}=\mathrm{NOK}\,\vert\,\mathcal{E})=$ **1.0**	
					$P(\mathrm{SE02}=\mathrm{NOK}\,\vert\,\mathcal{E})=$ **1.0**	
					$P(\mathrm{SE03}=\mathrm{NOK}\,\vert\,\mathcal{E})=$ **1.0**	
					$P(\mathrm{SE04}=\mathrm{OK}\,\vert\,\mathcal{E})=$ **1.0**	
20	IO_6	{FC03 = True}	{F02 = FM02, FU01 = OK, FU02 = NOK, SE01 = NOK, SE02 = NOK, SE03 = OK, SE04 = NOK}	0.0187 ± 0.0015	$P(\mathrm{F02}=\mathrm{FM02}\,\vert\,\mathcal{E})=$ **0.9800**	✓
					$P(\mathrm{FU01}=\mathrm{OK}\,\vert\,\mathcal{E})=$ **0.9999**	
					$P(\mathrm{FU02}=\mathrm{NOK}\,\vert\,\mathcal{E})=$ **0.9990**	
					$P(\mathrm{SE01}=\mathrm{NOK}\,\vert\,\mathcal{E})=$ **0.9990**	
					$P(\mathrm{SE02}=\mathrm{NOK}\,\vert\,\mathcal{E})=$ **0.9990**	
					$P(\mathrm{SE03}=\mathrm{OK}\,\vert\,\mathcal{E})=$ **0.9999**	
					$P(\mathrm{SE04}=\mathrm{NOK}\,\vert\,\mathcal{E})=$ **0.9990**	

The mean of the inference time ± standard deviation is reported in milliseconds for each set of evidence based on 100 repeated measurements (cf. Section 6.4.4)

Appendix C Sensitivity analysis

We conducted a sensitivity analysis for the two sample fault cases presented in Sections 6.4.1 and 6.4.2 to validate the robustness of the decision behavior of the proposed BN. We used the sensitivity analysis according to Kjærulff & van der Gaag [41] which is supported by the GeNIe software tool. Table 8 summarizes the result of the sensitivity analysis for the sample fault case 1 as given by Table 2. The reachable probability ranges (third column in Table 8) of the different target node states are small or even zero if the values of the influencing parameters are changed by $\pm 10\,\%$. These small reachable probability ranges indicate that the decision behavior of the BN is very robust against $\pm 10\,\%$ changes of the identified parameters (last column in Table 8).

Table 9 summarizes the result of the sensitivity analysis for the second sample fault case as given by Table 3. As the previous sensitivity analysis for the first sample fault case show, this result also demonstrates small reachable probability ranges indicating that the BN's decision behavior is robust to changes in the identified parameters of $\pm 10\,\%$.

In general, sensitivity analyses are very context-dependent, i.e., they depend on (1) a specific set of target nodes and target states, (2) the set of evidence entered into the BN, (3) the current probability parameters and (4) the specified parameter spread (e.g., $\pm 10\,\%$) of the current values of the influencing parameters. As a result, there exist a very high multitude of possible sensitivity analyses for our BN, where each providing very specific insights to the given set of evidence and query node. In this work, we just report the results of the two sensitivity analysis conducted for the two sample fault cases. If required, the reader can conduct further sensitivity analyses for the BN presented for any set of evidence and any query nodes by using the supplementary material provided via GitHub (cf. Section 6.3).

Table 8 Result of the sensitivity analysis for sample fault case 1 presented in Section 6.4.1

Target nodestate	Current probability value	Reachable probability range	Influencing parameter[±10 % parameter range]
FC06 = True	0.900736	[0.89091, 0.908939]	FC06 = True : [9e-06, 1.1e-05]
		[0.908923, 0.892695]	FC05 = True : [9e-07, 1.1e-06]
FE03_FC07 = False	0.997892	[0.998092, 0.997692]	FC07_FE03 = True | F01 = OK : [0.0018, 0.0022]
		[0.997902, 0.997882]	FC02 = True : [9e-05, 0.00011]
		[0.997893, 0.997891]	FC01 = True : [9e-06, 1.1e-05]
		[0.997892, 0.997892]	FC07_FE03 = True | F01 = UNK : [0.18, 0.22]
		[0.997892, 0.997892]	FC05 = True : [9e-07, 1.1e-06]
FC08 = False	0.99999	[0.9999991, 0.999989]	FC08 = False : [9e-06, 1.1e-05]
		[0.99999, 0.99999]	FC06 = True : [9e-06, 1.1e-05]

The parameter spread is set to 10 % of the current values of the influencing parameters. Set of evidence: {F03 = FM03, FC04 = False}. Set of target nodes: {FC06, FE03_FC07, FC08}

Table 9 Result of the sensitivity analysis for sample fault case 2 presented in Section 6.4.2

Target nodestate	Current probability value	Reachable probability range	Influencing parameter[±10 % parameter range]
FC02 = True	0.908257	[0.899091, 0.915896][0.916581, 0.9000892]	FC02 = True : [9e-05, 0.00011]FC01 = True : [9e-06, 1.1e-05]
FE03_FC07 = True	1.0	[1.0, 1.0]	-
F03 = FM04	0.97974	[0.979715, 0.979765][0.979741, 0.979739][0.97974, 0.97974][0.97974, 0.97974]	FC04 = True : [0.00045, 0.00055]FC06 = True : [9e-06, 1.1e-05] FC05 = True : [9e-07, 1.1e-06]FC08 = True : [9e-06, 1.1e-05]
FE07 = True	0.983778	[0.98378, 0.983776][0.983778, 0.983778][0.983778, 0.983778][0.983778, 0.983778]	FC04 = True : [0.00045, 0.00055]FC06 = True : [9e-06, 1.1e-05] FC08 = True : [9e-06, 1.1e-05]FC05 = True : [9e-07, 1.1e-06]

The parameter spread is set to 10 % of the current values of the influencing parameters. Set of evidence: {F01 = FM01}. Set of target nodes: {FC02, FE03_FC07, F03, FE07}

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Declarations

Competing Interests The authors state no conflict of interest.

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